Complex Analysis of Combat in Afghanistan

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Abstract

Detrended fluctuation analysis (DFA), a modern technique for examination of complex systems, was applied to combat related data in Afghanistan for the epoch 2002-2009. To detect long-term correlations in the presence of trends, we apply DFA that is able to systematically detect and overcome nonstationarities in the data at all timescales. The objective was to determine whether the nature of combat in Afghanistan, as observed by NATO forces, is fractal in its statistical nature. In every instance we found strong power law correlations in the data, and were able to extract accurate scaling exponents. On the other hand, a decrease in hostilities is likely to persist from one day to the next. We find a measure of predictability inherent in the dynamics of the combat system - there is a history or memory in the signal so that the future dynamics are not random but correlated with past events. This is seen most strongly for Att and d events, and only weakly for is and id events.

Résumé

L’analyse des fluctuations redressées (detrended fluctuation analysis, DFA), une méthode récente d’analyse des systèmes complexes, a été appliquée aux données relatives aux combats en Afghanistan pour la période allant de 2002 à 2009. Afin de détecter des corrélations à long terme en présence de tendances, nous avons utilisé la DFA, qui permet de détecter et de contourner systématiquement la non stationnarité des données dans toutes les échelles temporelles. L’objectif était de déterminer si la nature des combats en Afghanistan, telle qu’elle a été observée par les forces de l’OTAN, présente un caractère statistiquement fractal. Dans tous les cas, nous avons trouvé dans les données de fortes corrélations de loi de puissance et nous avons été en mesure d’extraire des exposants d’échelle précis. Par ailleurs, une diminution des hostilités persiste généralement le lendemain. Nous avons également trouvé une mesure de prévisibilité inhérente à la dynamique du système de combat — il existe en effet une dimension historique ou une dimension de mémoire dans le signal, si bien que la dynamique future n’est pas aléatoire mais bien corrélée avec les événements passés. Ce phénomène est constaté plus fréquemment dans le cas des événements ATT et d, et plus rarement en ce qui concerne les événements is et id.

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Executive summary

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Background and Methodology

The analyzed combat data comprise events occurring in Afghanistan during the NATO deployment from 2002 to the present. The exact nature of the events was not disclosed for security reasons. The provided data record daily combat-related events in terms of geographical location and frequency. There is an evident increasing trend in the daily count of hostilities. The data give evidence of intermittency, and of long-range dependence and nonstationarity. To avoid spurious detection of correlations due to data nonstationarity, a detrended fluctuation analysis was employed. The idea of the method is to subtract possible deterministic trends from the original time series and then analyze the fluctuation of the detrended data.

Results

In this analysis fluctuations in combat related data (from NATO) from Afghanistan for 2002 to 2009 were studied. In all cases it was found that the detrended fluctuation functions were linear over about two decades in log-log space, and no crossover in scaling behaviour was observed.

The results indicate that a universal long-range power-law correlation may exist which governs Afghanistan combat variability at all temporal scales. In every instance it was found strong power law correlations in the data, and were able to extract accurate scaling exponents, α. The case $\alpha<0.5$ corresponds to long-term anti-correlations, meaning that large values are most likely to be followed by small values and vice versa. This is not the case in the combat data. Instead, $\alpha>0.5$ indicating long-range correlations. This suggests that the size of combat events is correlated, a large offensive is likely to follow by increased hostilities the following day. On the other hand, a decrease in hostilities is likely to persist from one day to the next. The important message to take from this analysis is that there is a measure of predictability inherent in the dynamics of the combat system - there is a history or memory in the signal so that the future dynamics are not random but correlated with past events. This is seen most strongly for *Att* and *d* events, and only weakly for *is* and *id* events[*]. For longer term, or larger scale, planning purposes it is also relevant to note that strong correlations also exist in the *All* data category, which summarizes the totality of hostile events.

[*] *Att* stands for all kinetic events (attacks), *d* stands for direct fire events, *is* and *id* stand for improvised explosive devices secured and discovered, respectively.

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Contexte et méthodologie

Les données sur les combats qui ont été analysées recouvrent les événements survenus en Afghanistan lors du déploiement des troupes de l’OTAN, de 2002 jusqu’à maintenant. La nature exacte des événements n’a pas été dévoilée pour des raisons de sécurité. Les données fournies font état d’événements relatifs aux combats quotidiens en termes de localisation géographique et de fréquence. Le nombre des affrontements quotidiens suit une nette tendance à la hausse. Les données témoignent d’une intermittence, d’une dépendance statistique à long terme et d’une non-stationnarité. Afin d’éviter la fausse détection de corrélations imputable à la non-stationnarité des données, nous avons eu recours à l’analyse des fluctuations redressées (DFA). La méthode consiste à soustraire les possibles tendances déterministes de la série temporelle initiale, puis à analyser les fluctuations des données ainsi redressées.

Résultats

Le but de la présente analyse était d’étudier les fluctuations des données relatives aux combats (de l’OTAN) en Afghanistan de 2002 à 2009. Dans tous les cas, nous avons observé que les fonctions de fluctuations redressées étaient linéaires sur une période d’environ deux décennies en coordonnées log-log et qu’aucun changement n’était survenu dans le comportement d’échelle. Les résultats indiquent qu’une corrélation de loi de puissance universelle à long terme peut exister et influencer la variabilité des données sur les combats en Afghanistan dans toutes les échelles temporelles. Dans tous les cas, nous avons observé de fortes corrélations de loi de puissance dans les données et nous avons été en mesure d’extraire des exposants d’échelle précis, α. Le cas $\alpha<0{,}5$ correspond aux anti-corrélations à long terme, indiquant que des valeurs élevées sont généralement suivies de valeurs faibles et vice-versa, ce qui n’est pas le cas des données relatives aux combats. La relation $\alpha>0{,}5$ indique plutôt la présence de corrélations à long terme. Ce résultat donne à penser que la taille des événements relatifs aux combats est corrélée, une grande offensive étant généralement suivie d’un accroissement des hostilités le jour suivant. Par ailleurs, une diminution des hostilités persiste généralement le lendemain. La présente analyse permet principalement d’établir qu’il existe une mesure de prévisibilité inhérente à la dynamique du système de combat – il existe en effet une dimension historique ou une dimension de mémoire dans le signal, si bien que la dynamique future n’est pas aléatoire, mais corrélée avec les événements passés. Le phénomène est particulièrement fréquent dans le cas des événements ATT et d, et plus rare en ce qui concerne les événements is et id. Pour les besoins de la planification à plus long terme, ou à plus grande échelle, il est également intéressant de noter l’existence de fortes corrélations dans la catégorie TOUTES LES DONNÉES, qui résume l’ensemble des événements hostiles.

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1. Introduction

1.1. Background

The complex nature of natural objects has only in relatively modern times been realized. Objects and systems as dissimilar as clouds, mountain ranges, lightning bolts, coastlines, space plasmas snow flakes, various vegetables, the human lung and brain, and stock markets all display statistical behavior that can be described by the term ‘fractal.’ The term was coined in 1975 by Benoit Mandelbrot [Mandelbrot, 1975] to describe data in natural and mathematical systems which have heavy-tailed distribution functions and a self-similar statistical structure. The concept of fractals provides bridges over the chasms that now separate mathematics, science and technology from one another and from the interests of humanity.

Numerous studies have demonstrated that fractal geometry serves as a ubiquitous design principle in biological organisms [West et al., 1986; Uritsky and Muzalevskaya, 1995]. Fractal geometry allows structures to be quantitatively characterized in geometric terms even if their form is not even or regular, because fractal geometry deals with the geometry of hierarchies and random processes. The essential characteristic of fractals is that as finer details are revealed at higher magnifications the form of the details is similar to the whole: there is self-similarity. In human physiology the internal membrane surface of cells [Weibel, 1991], or the inner lung surface [Boser et al., 2005], are difficult to describe in terms of classical geometry, but they exhibit properties describable by fractal geometry. Fractal structure has been studied in numerous contexts including the arterial branching system in the kidney, the alimentary tract, the bile duct system, in nerves and muscles such as the heart, and the convoluted surface of the brain [Bassinghwaite et al., 1994]. Concepts of fractal geometry proved exceptionally useful in characterizing the structure of branching anatomic structures, such as those found in pulmonary airways and in blood vessels [Peitgen et al., 1990]. A similar design principle has been revealed in many other structures, including the His-Purkinje system responsible for electric cardiac stability [Goldberger et al., 1985], interface surfaces of biological tissues, and neuron networks of the brain and nervous system [Bieberich, 2002].

Even more importantly, fractal organization is not limited to spatial structures and involves temporal behavior of many physiological functions. Electroencephalogram (EEG) observations, which measure neural activity via voltage changes on the scalp, or even closer to the brain surface [Le Van Quyen et al., 2001], have repeatedly provided strong evidence of fractal dynamics during different cognitive or psychomotor activities [Babloyantz and Destexhe, 1987], as do functional magnetic resonance images [Eguíluz et al., 2005] and studies of low-frequency heart rate variability [Kobayashi and Musha, 1982; Baumert, 2007]. Fractal fluctuations are indicative of a biomolecular organization [Villani et al., 2000] as well as of behavioral responses to external stimuli and cognitive tasks [Amaral et al., 2001; Goldberger et al., 2002]. It has also been found [Ivanov et al., 2001] that normal physiological conditions are typically characterized by the most “perfect” and broad-band fractal patterns described by certain values of fractal exponents, whereas pathological states tend to produce “broken” fractals with distinct scaling distortions and/or abnormal exponents [Peng et al., 1993; 1995; Tulppo et al., 2005].

These data strongly suggest that fractal fluctuations in the human organism are not a “statistical noise” but are signatures of fundamental processes that maintain stability of physiological functions and their response to external perturbations. It seems that fractal fluctuations are, in fact, necessary for a biological system to function properly.

In every case listed the dynamics of human action and development are facilitated by key cognitive skills such as the aptitude to generalize, abstract, reuse, reorganize and apply knowledge learned in previous life experiences to novel situations. Since the fractal experience is so widespread in human physiology, decision making, and practice, we wish to determine if similar statistics are a property of the most dangerous and critical of human interactions and responses, viz. military combat.

1.1.1. Decision Making: Mind in Motion

In order to study military combat data, one needs to recognize that decisions made by human beings are a complicated product of multiple factors, almost all mediated by the human mind. Minds are complex systems and, as such, are not commonly studied in the framework of physics, which perennially operates at the reductionist level on primitive fundamental units. The functionalist approach appreciates that the essence of mind is not the "hardware" at its mammoth or miniscule scales, but the dynamics and organization of the materiel (interacting "software" program). The mind is holistic, i.e. the living being operates as a unified system. Though it is complex, this reality does not necessarily imply that the complex decisions flowing from the brain are too complicated to understand, at least in part. An understanding of the mental decision making process can thus serve as a guide for study of the outcomes and dynamics of combat.

For some time it has been recognized that computational analysis will play an important role in elucidating the nature of human decision making. Recent studies of artificial neural networks have revealed that the rules of interaction between the "neurons" in the network can lead to interesting emergent behaviour compatible with fractal dynamics of learning and cognition [Chialvo and Bak, 1999]. The work by Kinouchi and Copelli [2006] suggested a mechanism to explain how humans are able to respond without difficulty to inputs that are extremely different in amplitude and range. They treated individual neurons as cellular automata randomly coupled to other neurons. The rules for the automaton result in sensitivity to wide intensity ranges, mimicking observations for humans, provided the neuronal network was critical. That is to say, the model produced realistic results provided the system was in a state where changes could rapidly propagate on all scales. These and many other simulation results strongly suggest that Turing's [1947] idea that the brain may function near a critical state seems to have potential for finally bearing fruit. In many cases, the neuron networks should be critical in order to ensure a proper level of plasticity, sensitivity, functional stability and learning skills. This theoretical view is reinforced by a growing body of observational evidence of fractal fluctuations in the central nervous system which can be a marker of self-organized critical dynamics of interacting ensembles of brain cells. All of these lines of evidence suggest that, at a fundamental level, human decision making in military combat is amenable to study via complex analysis.

1.1.2. Decision Making: Combat Data

Our combat data comprise events occurring in Afghanistan during the NATO deployment from 2002 to the present. We are uncertain as to the exact nature of the events, as these have not been disclosed. However, we have data that record daily combat related events in terms of geographical location and frequency.

Our data set, which we call the Daily set, comprises the number of combat related events for each day. These data were provided by Dr. Peter Dobias, DRDC-CORA. Because the data record only that an event has occurred during a day, and not when during the day, we are not able to create a finer temporal data set, but only the total events per day. As the military mission has proceeded the number of enemy contacts and events have increased. During the interval between 1 January and 31 July 2009 - 211 days - there were a total of 18,043 events of all types.

There are many days with multiple events. This is evident, as well as an increasing trend in the daily count of hostilities, from Figure 1. Here we show the entire roughly 7 year total event time series used in this study for All events (red), for all events associated with Kandahar (blue), and Helmand (green). These data give evidence of intermittency, and of long-range dependence and nonstationarity. The intermittency is suggested most clearly (because of scale in the figure) by the sudden jumps, or flights in the data for all events (red). This can be seen, for instance, in the sudden jump to over 60 events/day at the start of 2005, or the precipitous decrease at the end of the series from above 150 events/day to below 60 events/day. Long-range dependence is suggested by the longer-period trends, for instance during much of 2009.

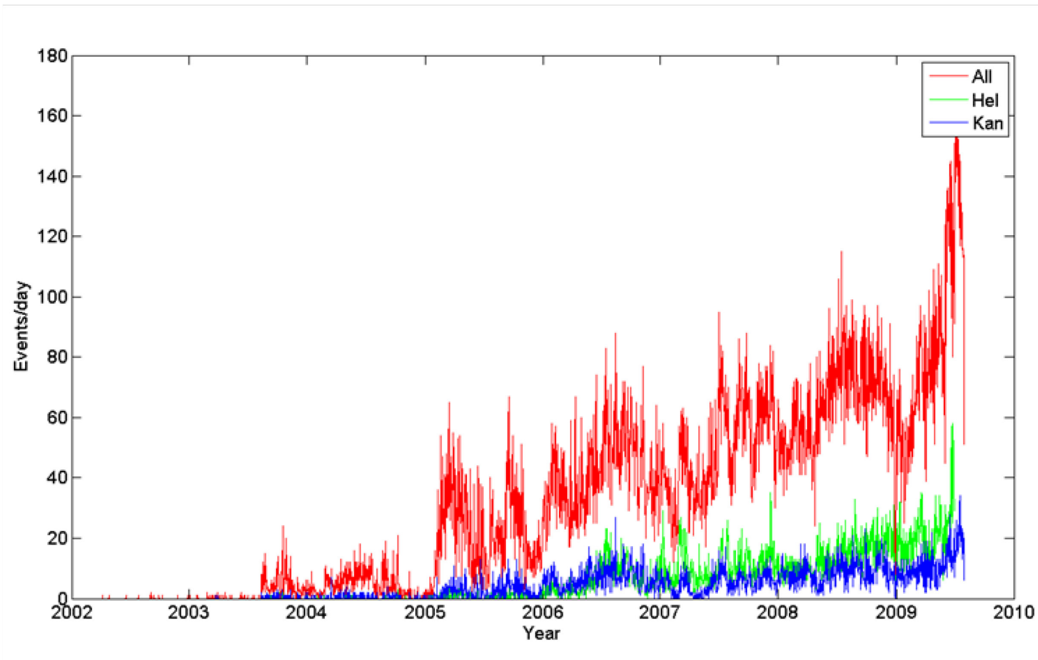

Figure 1. *Daily total number of combat incidents in Afghanistan, as recorded by NATO forces (red). Total daily events are also recorded for Kandahar (blue) and Helmand (green).*

Although human decision making is complex and multifaceted these data show evidence, in terms of their statistical fluctuations, that suggest some measure of predictability, and not merely in the obvious long-term trend. This is more remarkable given that the event data include complex nonlinear feedback interactions between hostile and friendly forces in combat.

1.2. Aim and Objectives

The main objective of the work was to calculate Hurst coefficient for the incident data from Afghanistan and subsequently to determine if the data is persistent or anti-persistent from the point of view of long-term correlations.

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2. Methodology

Long-range correlations can be tested for in numerous ways. A general methodology is to estimate how a fluctuation measure, denoted here by F, scales with the size n of the time window considered. Specific methods, such as Hurst's rescaled range analysis [Hurst, 1951], power spectral analysis, structure function analysis [Abramenko et al., 2002], or detrended fluctuation analysis (DFA) [Peng et al., 1995], all essentially calculate such a fluctuation measure, although the measure is different for each technique. If the time series is stationary, we can apply standard spectral analysis techniques and calculate the power spectrum *E(f)* of the time series B_α as a function of the frequency *f*. For long-term correlated data that follows a fractional Brownian motion (fBm) the relationships between the scaling exponents of the various methods are simple. For instance, for stationary data, from spectral analysis we have $E(f) \sim f^{-\beta}$ where $\beta = 2H - 1 = 1 - \gamma$, with *H* being the Hurst exponent, related to the correlation exponent γ. Usually, real-world data are not stationary, and therefore it is completely inappropriate to use techniques like spectral analysis. In this case modern methods, such as DFA have been developed. In DFA, the fluctuation function varies as, $F \propto n^\alpha$, where α is the scaling exponent. For a time series that tends to follow a fBm the relationship is $\alpha = H$.

A signal that displays fBm is one that has a zero-mean, and which can be expressed as the stochastic integral [Mandelbrot and Van Ness, 1968]

$$(1) \qquad B_\alpha(t) = \frac{1}{\Gamma(\alpha + 1/2)} \left\{ \int_{-\infty}^{0} [(t-s)^{\alpha-1/2} - (-s)^{\alpha-1/2}] dW(s) + \int_{0}^{t} (t-s)^{\alpha-1/2} dW(s) \right\}$$

where Γ is the gamma function, and *W* is a white noise process defined on $(-\infty,\infty)$. Here $\alpha \in (0,1)$ is the scaling exponent. Larger values closer to 1 result from signals that are relatively smooth, and smaller values closer to 0 are very rough. The covariance function for the fBm signal is given by

$$(2) \qquad \operatorname{cov}\{B_\alpha(s), B_\alpha(t)\} = \frac{1}{2}\{|s|^{2\alpha} + |t|^{2\alpha} - |s-t|^{2\alpha}\}$$

so that $B_\alpha(0) \equiv 0$ and the variance $\operatorname{var}\{B_\alpha(t)\} = t^{2\alpha}$. This means that for the special case $\alpha=1/2$, fBm reduces to the well-known random walk of Brownian motion. Signals with scaling exponents above $\alpha=1/2$ are also called persistent, because if the data at some point have $B(t_{i+1})>B(t_i)$, for example, then the probability is greater than 0.5 that $B(t_{i+2})>B(t_{i+1})$. Signals with exponents below 1/2 are called antipersistent, or anticorrelated, because if $B(t_{i+1})>B(t_i)$, the probability is greater than 0.5 that $B(t_{i+2})<B(t_{i+1})$. Typically, fBm is nonstationary, and thus detection of the presence of memory is a delicate task. Nonstationarity means that the statistical properties are not constant through the signal, and traditional analysis methods, that assume stationarity (e.g. power spectra), cannot be used. Notwithstanding the difficulties, fBm has been observed in a variety of fields, including hydrology [Neuman and Federico, 2003], geophysics [Frisch, 1997], biology [Collins and De Luca, 1994], telecommunication networks [Taqqu et al., 1997], and others. We will employ DFA to the combat data to test whether their behaviour is consistent with a fBm.

Novel ideas from statistical physics led to the development of DFA [Peng et al., 1995]. The method is a modified root mean squared analysis of a random walk designed specifically to be able to deal with nonstationarities in nonlinear data, and is among the most robust of statistical techniques designed to detect long-range correlations in time series [Taqqu et al., 1996; Cannon et al., 1997; Blok, 2000]. DFA has been shown to be robust to the presence of trends [Hu et al., 2001] and nonstationary time series [Kantelhardt et al., 2002; Chen et al., 2002]. This makes DFA appropriate to many natural signals that are heterogeneous, and exhibit different types of nonstationarities. In the case we examine here, the combat data is highly nonstationary displaying all the complexity inherent in data produced by the nonlinear feedback due to human interactions.

Briefly, the DFA methodology begins by removing the mean, $\overline{B}$, from the time series, *B(t)*, and then integrating

$$y(k) = \sum_{t=1}^{k}[B(t) - \overline{B}] \tag{3}$$

The new time-series is then divided into boxes of equal length, *n*. The trend, represented by a least-squares fit to the data, is removed from each box. The trend is typically a linear, quadratic, or cubic function [Hu et al., 2001; Vjushin et al., 2001]. Box *n* has its abscissa denoted by $y_{n,m}(k)$. Next the trend is removed from the integrated time series, *y(k)*, by subtracting the local trend, $y_{n,m}(k)$, in each box. The degree of the trend polynomial can be varied in order to eliminate constant (*m*=0), linear (*m*=1), quadratic (*m*=2) or higher order trends of the polynomial function. Conventionally the DFA is named after the order of the trend function polynomial (DFA0, DFA1, DFA2, ...). In DFA*m*, trends of order *m* in the polynomial fitting function and of order *m*-1 in the original record are removed.

For a given box size *n*, the characteristic size of the fluctuations, denoted by *F(n)*, is then calculated as the root mean squared deviation between *y(k)* and its trend in each box

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[y(k) - y_{n,m}(k)]^2} \tag{4}$$

This calculation is performed over all time scales (box sizes). A power-law scaling between *F(n)* and *n* indicates the presence of fractal scaling

$$F(n) \propto n^{\alpha} \tag{5}$$

where the parameter α is a scaling exponent. The scaling exponent can take values between 0 and 3/2; if $\alpha = 0.5$ the signal is white noise and there is no correlation in the data; $\alpha < 0.5$ indicates anti-correlated meaning that large values are most likely to be followed by small values and vice versa. Values of $\alpha > 0.5$ indicate correlated time series. The larger the value, the more persistent and smooth is the time series. When $\alpha \approx 1$ the signal corresponds to a pink noise. Pink noise corresponds to a time series with 1/f power spectrum, although as we mentioned above the nonstationary nature of the data would render spectral analysis spurious. Numerous mechanisms and processes produce 1/f noise in nature and inhuman physiology [West and Schlesinger, 1990]. Visually anti-correlated data presents a very rough profile as compared to smoother profiles with correlated data.

3. Results

In any numerical analysis of real data one must always remain aware of the caveats intrinsic to a given methodology. This assumes, naturally, that the methodology may be legitimately applied. For instance, spectral methods are inappropriate and will yield results that are spurious or without merit. On the other hand, for our data the methods introduced in the previous section yield results that are trustworthy, provided care is taken to test for all possible causes that can make the method fail. In short, to understand the intrinsic dynamics of a given system, it is important to analyze and correctly interpret its output signals. Many records do not show simple monofractal scaling, but in other cases there are crossover timescales separating regimes with different scaling exponents. For example, there can be one type of correlation at long timescales and another at small scales. To be sure one can reliably detect long-range correlations, it is important to differentiate trends from the long-range fluctuations intrinsic in the data. An artificial crossover in the fluctuation function usually can arise from a change in the correlation properties of the signal at different time or space scales, or can often arise from trends in the data. Trends can thus lead to a false detection of long-range correlations. In thinking of the combat arena in terms of a complex physical system, one needs to recognize that trends may arise from the intrinsic dynamics of combat rather than being an epiphenomenon of external conditions. As more of the enemy become involved in the combat effort, one might initially expect an increasing trend for conflict that might be smooth and monotonous or slowly oscillating.

Figure 2 shows clearly that as the conflict with the enemy progressed in time, there has been a trend for an increase in events each day. Thus there is a corresponding downward trend in the time between events. Application of the DFA2 method to noisy signals without any polynomial trends leads to scaling results identical to the scaling obtained from the DFA1 method, with the exception of some vertical shift to lower values for the root mean squared fluctuation function. Similarly, polynomial trends of order lower than l superposed on correlated noise will have no effect on the scaling properties of the noise when DFAl is applied. Because of the obvious presence of trends in the data we therefore applied DFA1, DFA2, and DFA3 to be certain that our results are not a product of the analysis method. It is essential in the DFA-analysis that the results of several orders of DFA are compared as results are only reliable when above a certain order of DFA they yield the same type of behaviour.

Figure 3 shows the fluctuation function computed for all events in the conflict database. The top graph shows the fluctuation curves for all combat events, the middle graph shows curves for all Helmund events, and the bottom graph shows fluctuation curves for all Kandahar events. The blue, green, and red curves correspond, respectively, to m=1, 2, 3 for DFAm. Small deviations from the scaling law (Eqn. 5), i.e. deviations from a straight line in a double logarithmic plot, occur for small scales n, in particular for DFAm with large detrending order m. These deviations are intrinsic to the usual DFA method, since the scaling behaviour is only approached asymptotically. The deviations limit the capability of DFA to determine the correct correlation behaviour in very short records and in the regime of small n. Aside from all data events, we were also provided with data that discriminates between different types of events, viz. *att*, *d*, *id*, and *is* events[2].

[2] *Att* stands for all kinetic events (attacks), *d* stands for direct fire events, *is* and *id* stand for improvised explosive devices secured and discovered, respectively.

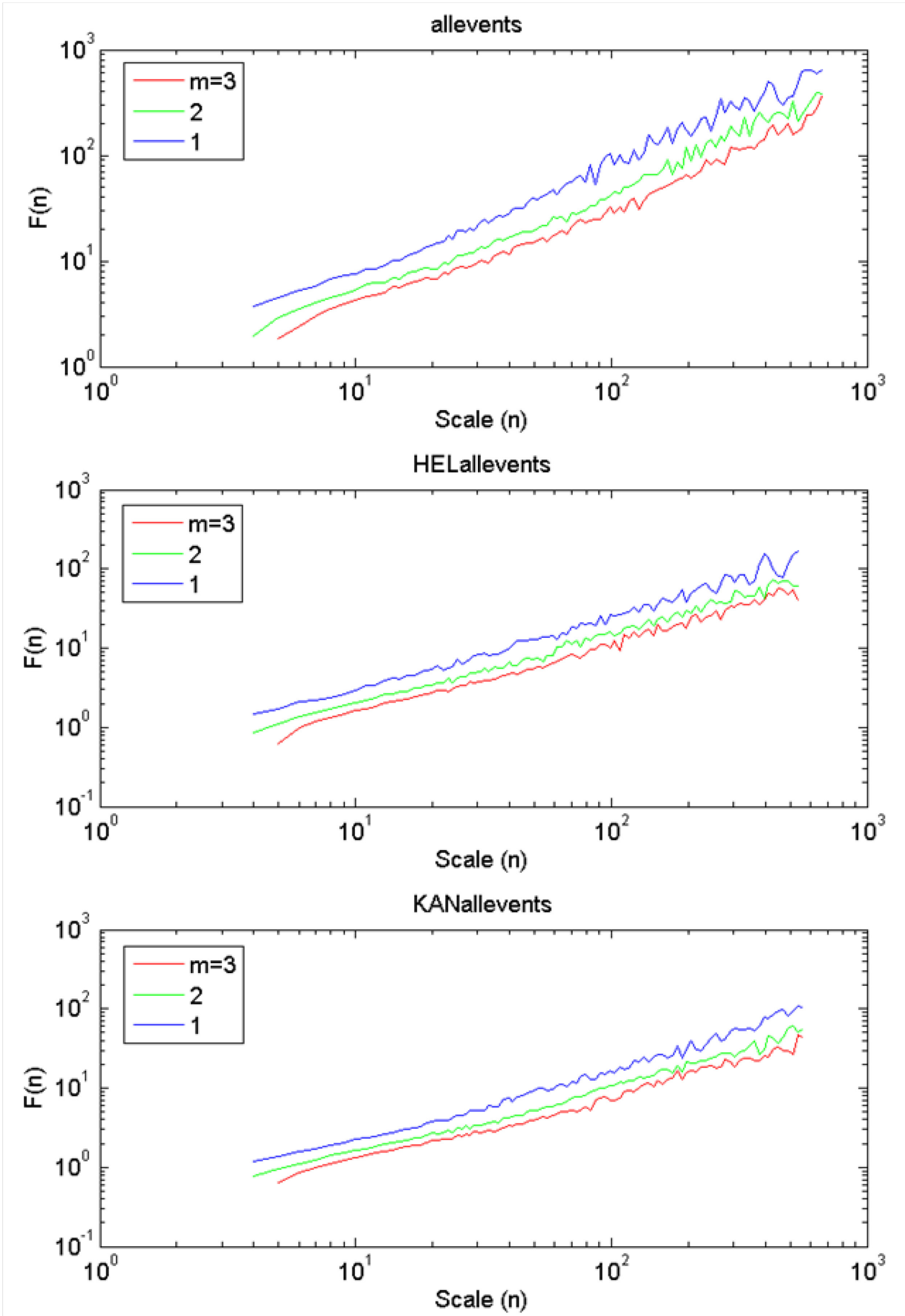

Figure 2. *Fluctuation functions for different orders of DFAm. The blue, green, and red curves correspond to m=1,2,3. In the upper plot the curves are for all combat events. The middle plot for all Kandahar events, and the bottom plot for Helmand data*

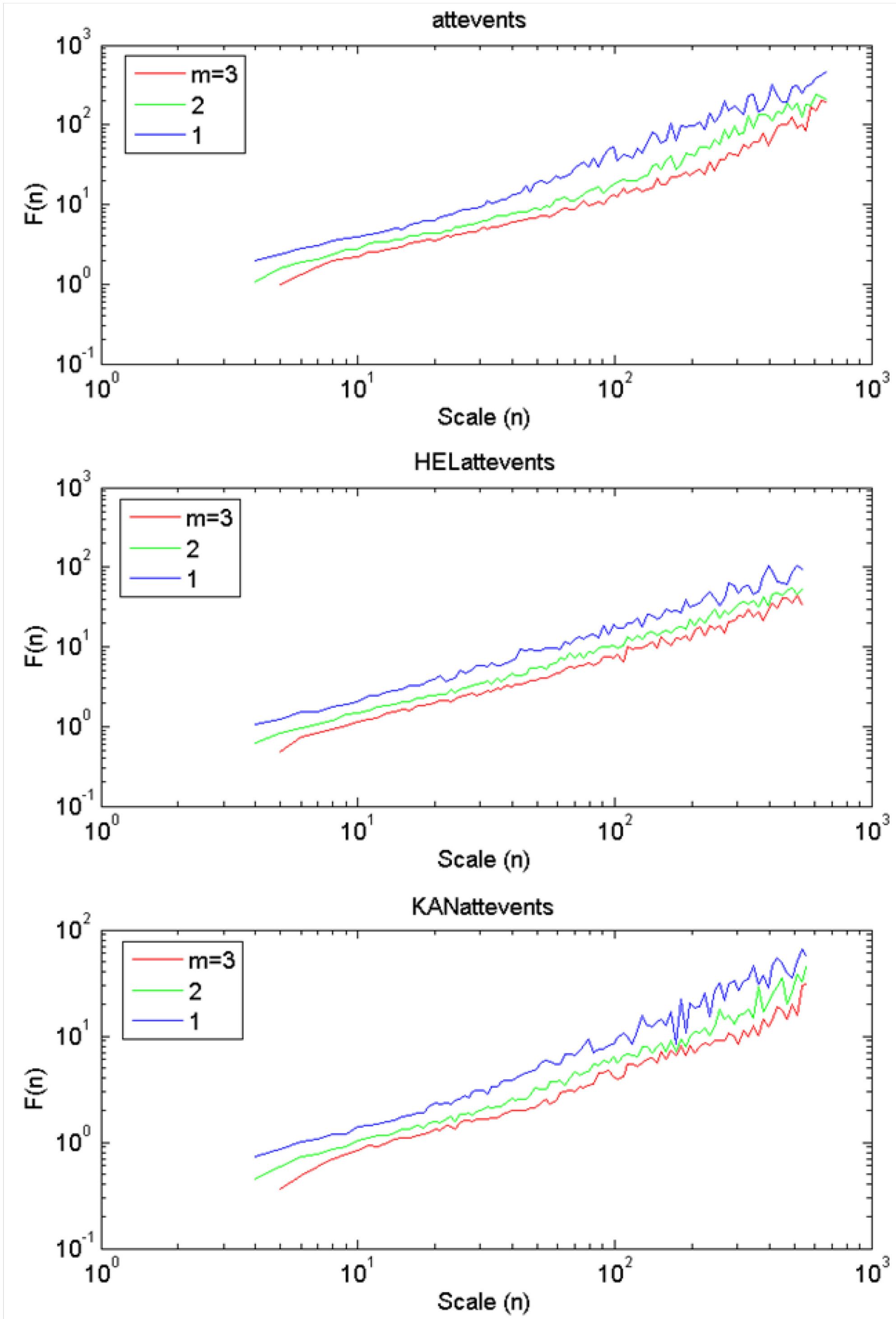

Figure 3. *Fluctuation functions for different orders of DFAm for att events. The blue, green, and red curves correspond to m=1,2,3. In the upper plot the curves are for all combat events. The middle plot for all Kandahar events, and the bottom plot for Helmand data events, and the bottom plot for Helmand data.*

For interest, Figure 4 shows the curves for *att* events, but since the other curves show essentially the same power law type of behavior they are not shown. Table 1 gives the results for the scaling exponents derived from these various curves.

Table 1. *Scaling exponents calculated for the various types of combat events. The third column shows the correlation coefficient computed from the linear least squares fit.*

Data type	α	r
All	1.093±0.016	0.9922
Hel All	0.986±0.017	0.9893
Kan All	0.995±0.012	0.9947
Att All	1.200±0.017	0.9923
Hel Att	0.982±0.016	0.9900
Kan Att	0.9840±0.020	0.9852
Hel d	0.973±0.016	0.9900
Kan d	0.988±0.019	0.9859
Hel id (m=2)	0.588±0.014	0.9819
Kan id	0.620±0.011	0.9876
Hel is	0.603±0.021	0.9580
Kan is	0.676±0.011	0.9912

We find that all events (the first three rows of Table 1) have a scaling exponent $\alpha \approx 1$, within the error. This is a remarkable result that suggests these data correspond to an 1/f noise, the implications of which will be discussed in the conclusion. *Att* , and *d* events between Helmand and Kandahar are statistically similar. Indeed, with the exception of *id* and *is* events, there are no statistical differences between the different subsets of events in Helmand and Kandahar. Not only are these two subsets (*is* and *id*) different between Helmand and Kandahar, but they are different from the rest of the data, having scaling exponents $\alpha \sim 0.6$.This indicates the presence of a different dynamics governing these events.

4. Summary and Conclusions

The persistence (correlation) of the certain natural data is well-known. For instance, in Mediterranean locations weather if one day is sunny and warm, there is a high tendency that the next day remains similar. Just as in physical systems fluctuations in the theatre of combat and warfare carry important information about the system. We have applied a novel methodology and treat the data from the combat spectrum like a time series.

In this analysis we have studied fluctuations in combat related data (from NATO) from Afghanistan for 2002 to 2009. To avoid spurious detection of correlations, due to data nonstationarity, we employed a detrended fluctuation analysis. The idea of the method is to subtract possible deterministic trends from the original time series and then analyze the fluctuation of the detrended data. In all cases we found that the detrended fluctuation functions were linear over about two decades in log-log space, and no crossover in scaling behaviour was observed. The results indicate that a universal long-range power-law correlation may exist which governs Afghanistan combat variability at all temporal scales. In every instance we found strong power law correlations in the data, and were able to extract accurate scaling exponents, α. The case $\alpha<0.5$ corresponds to long-term anti-correlations, meaning that large values are most likely to be followed by small values and vice versa. This is not the case in the combat data. Instead, $\alpha>0.5$ indicating long-range correlations. This suggests that the size of combat events is correlated, a large offensive is likely to follow by increased hostilities the following day. On the other hand, a decrease in hostilities is likely to persist from one day to the next. The important message to take from this analysis is that there is a measure of predictability inherent in the dynamics of the combat system - there is a history or memory in the signal so that the future dynamics are not random but correlated with past events. This is seen most strongly for *Att* and *d* events, and only weakly for *is* and *id* events. For longer term, or larger scale, planning purposes it is also relevant to note that strong correlations also exist in the *All* data category(Table 1, row 1), which summarizes the totality of hostile events.

The correlations found may be amenable to modelling after the manner of Wanliss et al. [2005] and Anh et al. [2007], although more data may be needed to achieve adequate statistical plausibility to the hazard forecasts. Thus, just as in weather forecasts, one might produce combat forecasts with probabilities assigned to certain events that may inform decision making. The combat processes may also be amenable to more detailed mathematical modelling. Since each event is a point process, the combat events could be considered a stochastic point process [Kaulakys and Meškauskas, 1998; Kaulakys et. al., 2005, 2009]. In these models the signal consists of pulses or events. The interpulse, interevent, interarrival, recurrence or waiting times of the signal are described by the general Langevin equation with multiplicative noise, which is also stochastically diffuse in some interval, resulting in the power-law distribution. Here the intrinsic origin of noise is in Brownian fluctuations of the mean inter-event time of the (Poisson-like) signal pulses, similar to Brownian fluctuations of signal amplitude that result in noise. The random walk of the inter-event time on the time axis is a property of randomly perturbed or complex systems that display self-organization.

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5. References

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List of symbols/abbreviations/acronyms

CORA	Centre for Operational Research and Analysis
DFA	Detrended fluctuation analysis
DND	Department of National Defence
DRDC	Defence Research and Development Canada
fBm	Fractal Brownian Motion